Artículo

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Comparing the Use of Scientific Software and Generative AI Art Tools: Exploratory research and future agenda

Comparación del uso de software científico y herramientas de arte de IA generativa: investigación exploratoria y agenda futura

Recibido: 11/11/2024
Aceptado: 09/04/2025

Cómo citar este artículo:
Queiroz, F. (2025) «Comparing the Use of Scientific Software and Generative AI Art Tools: Exploratory research and future agenda». Inmaterial. Diseño, Arte y Sociedad, 10(19), pp 96-121
DOI 10.46516/inmaterial.v10.240

Keywords:
generative artificial intelligence, scientific software, user interfaces, scientific practice, creative practice

Palabras clave:
arte conductivo, interacción táctil, encarnación, neurofilosofía, investigación basada en la práctica

Abstract

The introduction of Generative Artificial Intelligence (GenAI) image and text generators has brought a renewed and significant amount of attention to textual user interfaces. Platforms such as ChatGPT and Midjourney generate, respectively, text and images from verbal instructions typed by users in natural language and processed by Machine Learning models. The use of natural language in GenAI differs from scientific software use interfaces, usually operated through programming and scripting languages. Still, both computational science and generative art, in their own ways, replace traditional 'wet' processes with abstract, dematerialised ones.

Through an examination of existing literature and preliminary research on those practices, this paper discusses the potential in cross-pollinating principles and concepts from scientific software and generative art and design. It aims to propose new approaches to developing and using those tools, having in mind not only user interface paradigms in those systems, but similarities and differences between scientific, and art and design domains. It will explore the tensions between open and closed models, objectivity and subjectivity, and reproducibility and uniqueness, which are respectively associated with scientific and creative practices. Preliminary results suggest the need for policies and practices in Generative AI development that involve art and design professionals and ways to acknowledge and reward their domain expertise.

Resumen

La introducción de generadores de imágenes y texto de inteligencia artificial generativa (IAG) ha atraído una atención renovada y significativa a las interfaces de usuario textuales. Plataformas como ChatGPT y Midjourney generan, respectivamente, texto e imágenes a partir de instrucciones verbales escritas por los usuarios en lenguaje natural y procesadas mediante modelos de *machine learning*. El uso del lenguaje natural en IAG difiere de las interfaces de uso del software científico, generalmente operadas a través de lenguajes de programación y *scripting*. Aun así, tanto la ciencia computacional como el arte generativo, a su manera, reemplazan los procesos tradicionales "húmedos" por procesos abstractos y desmaterializados.

A través de un examen de la literatura existente y la investigación preliminar sobre esas prácticas, el presente artículo analiza el potencial de la polinización cruzada de principios y conceptos del software científico y el arte y diseño generativo. El objetivo es proponer nuevos enfoques para el desarrollo y uso de dichas herramientas, teniendo en cuenta no solo los paradigmas de las interfaces de usuario en esos sistemas, sino también las similitudes y diferencias entre los dominios científico y de arte y diseño. Se explorarán las tensiones entre modelos abiertos y cerrados, objetividad y subjetividad, reproducibilidad y unicidad, que se asocian respectivamente con prácticas científicas y creativas. Los resultados preliminares sugieren la necesidad de políticas y prácticas en el desarrollo de IA generativa que involucren a los profesionales del arte y el diseño, y formas de reconocer y recompensar su experiencia en el dominio.

1. Introduction

Recent years have seen a surge in Generative AI tools and their application in areas as diverse as science, business, art and education. Two major novelty factors in that technology are the quality and complexity of its output - such as images and text that could be taken as human-generated - and the ease of use for user input, which is often reduced to the typing of instructions in natural language - a practice known as 'prompting'. This approach differs from traditional user interfaces based on the WIMP (windows, icons, menus, and pointers) paradigm that has become the standard in personal computing since graphical user interfaces (GUIs) became available.

Passing written instructions to computer systems is far from being a new practice: before the advent of GUIs, both professional and personal computing relied on typing as interface, from command line interfaces (CLIs, which remain accessible through terminal windows in modern computer operational systems) to fully fledged programming languages. Although not very common in contemporary consumer software, CLIs and programming remain popular in scientific software, or computational science, for qualities and idiosyncrasies that are particularly required by that field.

Taking into consideration differences and similarities between traditional scientific software and emerging AI tools in creative practice, this paper compares principles and practices in computational science and generative AI art, focusing on requirements, experiences and interface paradigms, along with contrasting practices in both fields. As such, this research aims at: exploring the potential exchange of ideas between the fields of computational science and generative AI art; describing practices from those communities; and provoking a wider discussion on the emerging field of Generative AI, guided by the following research questions:

Q1: How do computational science and generative art and design differ in terms of their goals, requirements and values?

Q2: How do approaches to text-oriented UI compare between scientific software, and generative art and design?

Q3: What practices and principles from scientific software could benefit generative AI and vice versa?

In searching for answers to those questions, this study draws from literature on the use and development of scientific software and generative AI tools, as well as on primary research involving surveys with experts, users and developers in the computational science and design communities.

Throughout the next sections, this paper introduces scientific software and Generative AI tools and their applications in both fields, discusses concepts that can be applied to both contexts, presents the methodology and findings from preliminary investigations, and proposes an agenda for future initiatives and research.

2. Background

2.1 Scientific Software

In this article, *scientific software* means software developed exclusively for use in scientific research and work. Therefore, productivity software routinely applied to science (e.g., spreadsheet editors) are not included in this discussion. Scientific software is 'developed by scientists for scientists' (Sletholt *et al.*, 2012, p. 24), often developed, extended or maintained by scientists themselves (Hannay *et al.*, 2009; Pinto, Wiese and Dias, 2018). In this context, *computational science* describes scientific practices and experiments conducted through scientific software. There are, of course, different types of scientific software. This is not only due to the diversity of scientific domains that make use of computational resources, but also the different needs and stages throughout computational science research (Kovalchuk *et al.*, 2012), usually described as *modelling* (expressing the scientific problem in mathematical or computational terms), *simulation* (entering and submitting data to be processed through computational tasks), and *result analysis* (analysing and visualising simulation results and drawing insights from them). When operating scientific software, those stages might be associated with specific user interface requirements (Queiroz and Spitz, 2016)

Although revolutionary in terms of computational power, the use of computers in science is not a complete rupture with the history of modern science, but rather a culmination of the mathematisation that shifted science from real-life, empirical observations to increasingly abstract values and parameters (Bachelard, 1984), in effect dematerialising scientific enquiry itself. Scientific software might be, then, a prime example of an *object to think with*, as users not only look for results, but for insights (Heroux, 2022), often counting on the software to uphold the scientific theory, formulae and tools for analysis.

As far as usability and user experience go, there might be significant differences between scientific software and typical consumer software. More pronouncedly, ease-of-use (or lack thereof) is often and historically reported as a concern in scientific software (MacLeod, Johnson and Matheson, 1992; Ahmed, Zeeshan and Dandekar, 2014; Paul-Gilloteaux, 2023). Indeed, given the needs of domain-expert users, characteristics such as accuracy, correctness, reliability and transparency take precedence over polish and user-friendliness. Seeing it simply as more difficult to use, though, might be a misconception, as unpopular methods such as command-line interfaces can be more effective and less error prone than their visual counterparts (Howison and Herbsleb, 2011).

Textual input is, therefore, usually the main – and often *only* – means of user interaction with scientific software. That could be through the use of programming languages, scripts, and configuration files. Likewise, textual output is very frequent as well, whether for data visualisation, report generation or user logs – even though the generation of data display graphs and visual simulations are often supported.

Another important distinction between scientific and typical user software is the openness of the former, regarding source code and data. Reasons for that include the desire for constant updating by code developers (and the scientific community at large), as well as the scrutiny which scientific research undergoes, requiring peer review of source code as well as the theories underlining it. Indeed, open-source initiatives, later spread to all types of software, originated in the scientific software community. There is, of course, closed source software (often commercial) for technical and scientific work that does not share all of those characteristics. Yet even that type of software usually demands a level of specialisation and computer literacy similar to those created by scientists themselves as *end-user developers*. (Ko et al., 2011). In a sense, that is not too dissimilar to what happens in wet labs, where specialised equipment and laboratorial conditions must be expertly handled. Likewise, in a similar manner to wet labs, ways of using and developing scientific software can be very specific to their respective domains.

2.2 Generative AI Art Tools

Gen AI tools are capable of generating outputs of diverse modalities (textual, visual and so on) from data processed through machine learning techniques able to recognise patterns from input data that allow for the output of new content from descriptive prompts (Feuerriegel *et al.*, 2024). In that case, such tools' abilities to generate output – and the quality of that output – are directly related to the dataset used in their training, i.e., the quantity and quality of image files (in the case of image generation), as well as the metadata that helps describe, label and classify those images. It is important to note that this generation of Generative AI (GenAI) tools supported by Large Language Models (LLMs) is radically different to the techniques and practices associated with previous definitions of computer-based generative art, based on procedurality, which would often require artists to engage in scripting, programming and, overall, have higher levels of computer literacy (Boden and Edmonds, 2009). Therefore, the term *generative art and design* will describe visual outcomes produced through the current generation of LLM-supported tools.

Generative AI tools have been increasingly proposed as solutions for the generation of imagery in professional contexts, serving as a replacement for traditional photography and illustration (digital or otherwise).

User experience and usability of Generative AI tools are often designed to be as easy and natural as possible, with minimal friction for their users. Despite an increasing trend for multimodal prompting (allowing for prompts combining text, image, voice and even video), GenAI tools traditionally use input text as their main input mode. In the case of image generation, users are usually expected to type in sentences using natural language, describing what they would like to see as a result. An image is then synthetised by the AI tool, based on patterns detected during training. In this case, the quality of the output depends on the quantity and breadth of a training dataset that is capable of identifying both image content – such as 'computer monitor on an office desk' – and

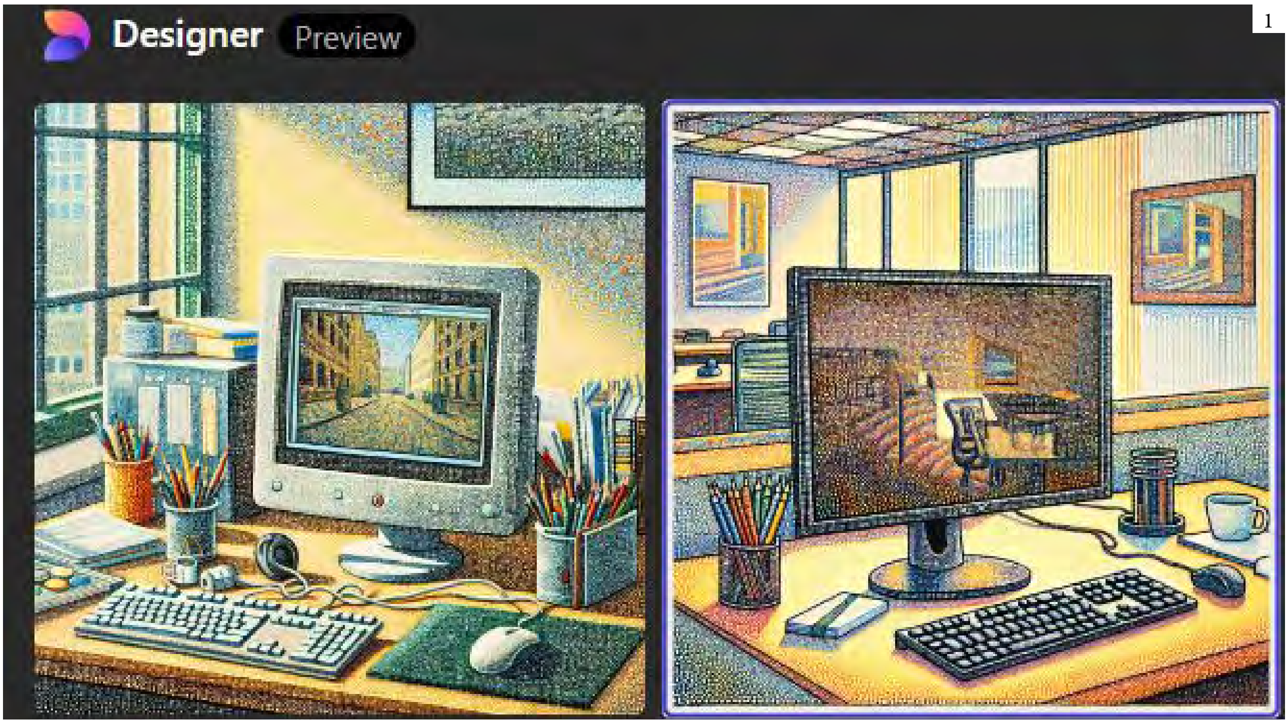

Figure 1 Microsoft Copilot's responses to an author's prompt: "Generate the image of a computer monitor on an office desk as painted by Georges Seurat"

style, for example, 'as painted by Georges Seurat' (Figure 1).

The emergence of Generative AI tools such as Midjourney, Microsoft Copilot and ChatGPT has become a hot topic, particularly regarding claims (from their proponents) of unparalleled creative productivity, but also attracting criticism on ethical grounds, considering copyright issues as well as negative economic impact on artists and illustrators.

2.3 Convergences and Contrasts

In addition to the original focus of this study on use (and user interfaces) of those systems, there are additional points of similarity and difference that deserve our attention:

On the one hand, Generative AI can be compared to computational science regarding its speed, as well as its distancing from real-life techniques and its move further towards mathematisation. As such, it requires a set of skills and way of thinking compatible with those systems.

On the other hand, in contrast to scientists - who might describe scientific software as a tool that allows them to do research that would otherwise be impossible (Segal and Morris, 2008; Hettrick *et al.*, 2014) - artists and illustrators often express their discontent, anxiety and hostility towards Gen AI tools that might not expand their creative skills but replace them altogether (Thomas and Gross, 2025). The financial weight of companies both investing in the development of AI tools (e.g., Microsoft, Google, OpenAI and Adobe) and the ones adopting them (e.g., Disney, Netflix and Ubisoft) suggests a stark contrast between the development of scientific software ('by scientists for scientists') and GenAI tools (by technology companies for businesses). This dissonance between GenAI proponents and the art and design community has been, indeed, perceived as a challenge to the research, as discussed in the following section.

3. Methodology

3.1 Introduction

This study mostly relies on bibliographic research and literature review, supported by a survey conducted through an online questionnaire. Regarding the study's research design, methods were used in a complementary manner. The online survey mostly addressed Q1 (goals, requirements and values), while bibliographic research was more strongly focused on Q2 (approaches to text-oriented UI design) and Q3 (potential benefits from practices and principles). Nevertheless, both methods contributed to answering all research questions.

Despite the focus on user attitudes towards work and software, a quantitative approach was preferred over qualitative methods at this stage, for the identification of the most pressing issues. A pilot focus group, not included in this analysis, was conducted later as a pilot for subsequent studies.

3.2 Bibliographic Research

A slightly greater focus on literature about the use of Generative AI is justified by the novelty of such practices, whereas scientific software use has been covered more extensively elsewhere. Material on AI image generation was identified through a search on SCOPUS and Web of Science databases for the following terms: 'prompt engineering' OR 'Dall-e' OR 'Midjourney' OR 'Stable Diffusion'. Initially focused on peer-reviewed journal articles, conference papers and chapters, it was expanded to include magazine and opinion articles, as well as material referenced by initial findings from the literature review.

3.3 Online Survey

Two separate online surveys collected answers from computational scientists (n=90), and digital artists or designers (n=57), aiming at identifying trends and attitudes towards their respective work practices, textual user interfaces and Generative AI tools. Limited sample size constitutes a limitation, suggesting additional quantitative research might be needed. Yet, the total number of participants (n=147) seems adequate, considering the novelty of the topic, the relatively small population of target groups and exploratory nature of the research. Data was collected through the JISC online surveys system and participants were recruited via mailing lists within the JISC community, University of Leeds mailing lists, and Facebook computational science communities, as well as GenAI communities on Facebook, x.com, reddit, artstation, and behance. As an incentive, six Amazon.co.uk vouchers (£50 value each) were given to random participants (three computational scientists and three digital artists or designers) after data was collected. Answers were collected between 17 October and 23 November 2023.

3.4 Research Challenges and Limitations

Throughout the research, there seemed to be an imbalance between the participation of computational scientists and that of Generative AI tool users. Admittedly, the proximity of the author with scientific software communities might have facilitated data collection from those groups. Yet, given the popularity of Generative AI tools, the lack of (authentic) response to the survey was somewhat surprising. In that sense, a main challenge in data collection was reaching out to Generative AI users, who are not so easy to find within the professional design community. This is both because of how recent those tools are, and due to the perceived stigma of art and design professionals using such tools, given the negative impact it could cause in their industry, as well as the lack of regard to authentic artistic skills attributed to the use of Generative AI tools.

An additional challenge in collecting such data was identifying communities of users who would answer the online survey on Generative AI use. Two issues arose from that. Firstly, online discussion forums hosted by Generative AI companies (Midjourney, Adobe Firefly) would not allow for links to academic research surveys to be publicised on their forums. Policies as this seem consistent with the closed-source, black-boxed model under which some big players in Generative AI industry work, often employing obscure opt-out policies and methods for scraping data (Goldman, 2023; Hammond, 2024; Ng, 2024).

A second issue regarding data collection was the number of fraudulent answers sent to the survey by automated bots, which we attribute to the dissemination of the survey on communities such as x.com and reddit. Data analysis, then, required extensive cleaning up of data obtained from the survey on Generative AI use. As the survey tool was targeted by automated bots, the exceedingly high number of fake entries (532, approximately 90% of total entries) had to be identified and removed from the database. In contrast, only one out of 91 entries from scientific software users was excluded (approximately 1%). Those entries were identified by the repetition of identical passages, across several entries, in answers to open questions; highly unlikely answers to demographic and professional background questions; as well as questions regarding open answers that were unrelated to the question's topic (for instance, 339 entries included the nonsensical answer 'a little tight on funds' to justify previous multiple-choice answers). Fake entries were removed before data analysis.

On another critical note, it seemed symptomatic that a database on Generative AI use was bombarded by repetitive, incorrect and fabricated information.

These shortcomings, although anecdotal, seem to reflect existing criticism of Generative AI and its industry, and might help support this study's rationale.

4. Findings and Discussion

Throughout the following subsections, we discuss the study's findings, taking into consideration both the literature review and survey results (Figure 2).

4.1 Computational Thinking and Prompt Engineering

A concept that has been associated to prompt engineering - and which could certainly be used to describe scientific software development and use - is *computational thinking*. This is a term proposed by Wing (2006) to describe an approach to problem-solving and critical analysis rooted in multiple layers of abstraction. A three-stage process devised for computer programming education structured computational thinking as *problem formulation* (abstraction), *solution expression* (automation), and *execution & evaluation* (analysis) – each stage being supported by appropriate tools (Repenning, Basawapatna and Escherle, 2016). Repenning and Grabowski (2023) argued that such a process could be adapted to prompting engineering for generative AI. In the case of prompting, *abstraction* comprises considering what

Figure 2 Answers to survey questions.

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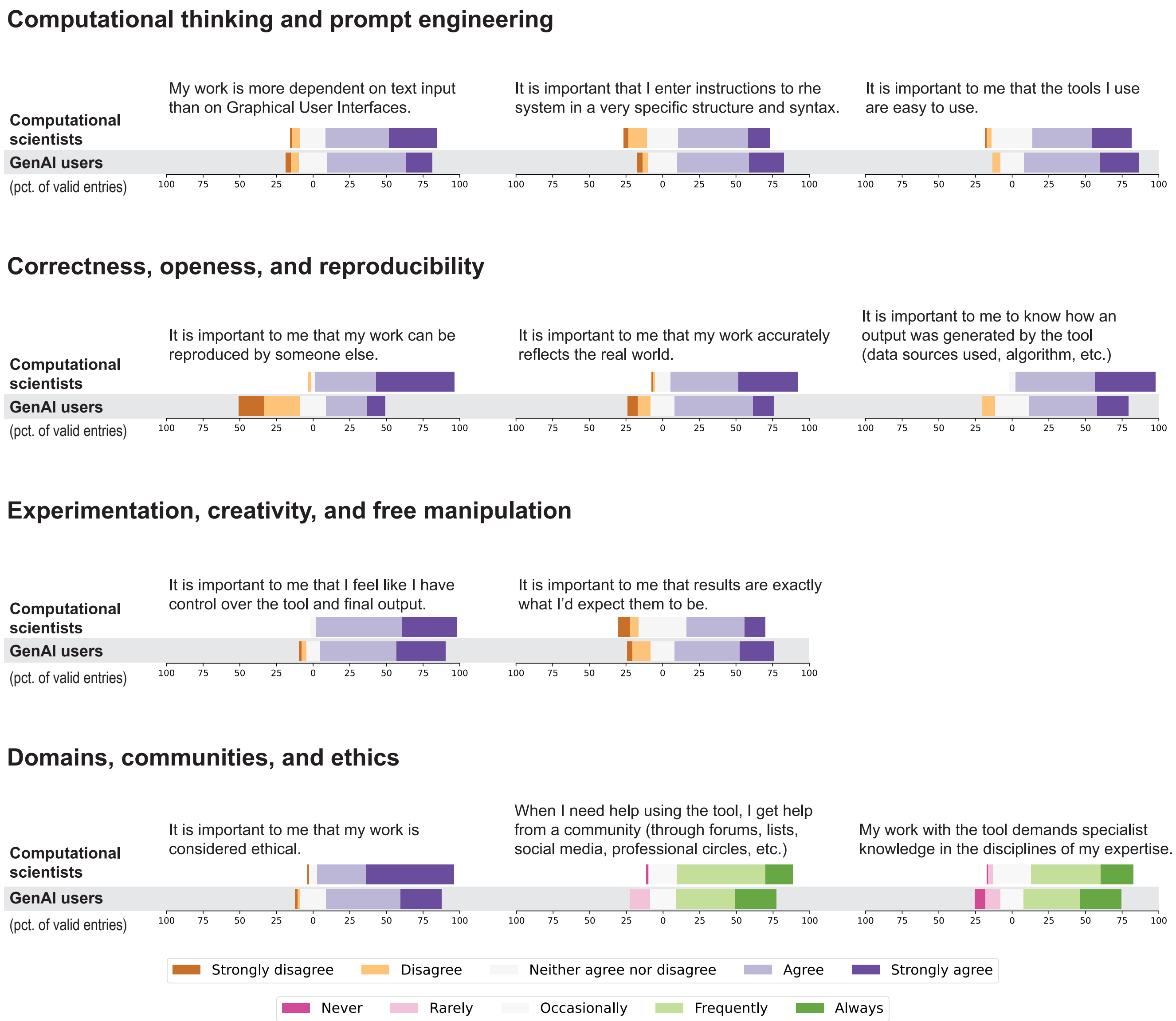

should the generative AI output answer to; *automation* involves generating and entering a prompt that might give a solution to the problem; and *analysis* means appraising AI output and choosing a suitable solution (or reiterating it through *automation*).

Parallels can be found between the computational thinking process and the stages of e-science described earlier, which consists of *modelling*, *simulation* and *result analysis* (Kovalchuk *et al.*, 2012), and although concepts of scientific theories and modelling in computational science might seem distant to the act of elaborating a prompt, both cases require an understanding of their respective paradigms (be those related to theories from a specific scientific domain, or to artistic representations, traditions and techniques). Moreover, as put by Repenning and Grabowski (2023), generative AI elevates the skill of elaborating and asking questions - arguably, another similarity with scientific practice, computational or not. We also note that scientific software occasionally facilitates the *modelling* and *simulation* phases through diagramming user interfaces and visual programming to complement (or link together) separate scripts and pieces of programming, eventually breaking from the textual interface paradigm (Cohen-Boulakia *et al.*, 2014; Fiannaca *et al.*, 2014)2014.

Ultimately, computational thinking should help users clearly express their intentions as either code or prompts that are adequate to their goals and tools. The differences between using programming and natural languages, however, might impact ease of use and the learning of those tools.

The quality of input text also deserves consideration. Although there is a significant emphasis on the use of natural (rather subjective) language, as opposed to programming (which is objective and unambiguous), the way in which prompts are engineered often mixes the use of language in conversational style with the addition GenAI tool parameters and scattered key terms of varying levels of objectivity. Take, for instance, the example from Papa *et al.* (2023) which combines styles, techniques and photographic equipment with adjectival interjections:

> *Headshot portrait of a young woman, real life, shot on iPhone, realistic background, HD, HDR color, 4k, natural lighting, photography, Facebook, Instagram, Pexels, Flickr, Unsplash, 50mm, 85mm, #wow, AMAZING, epic details, epic, beautiful face, fantastic, cinematic, dramatic lighting* (Papa et al., 2023, p. 13)

Those key terms refer to objective, technical aspects of the image generation ('50mm' film), sources of similar images ('pexels', 'flickr'), and terms that could be used to describe them subjectively ('AMAZING', 'beautiful face', etc.). Sanchez (2023) conducted a semantic analysis of text-to-images prompts that informed the creation of a taxonomy of prompt specifiers that categorises prompt terms as the following: subject; medium; influence (either genres, artworks, databases, or individual artists); light; colour; composition; detail (as in level of detail); and context.

Given the amount of detail included in prompts for image-to-text generation, it is interesting to notice that, in contrast, shorter prompts with no contextualisation ('zero-shot') can provide better results when analysing scientific large textual corpus in natural language, such as astronomical reports (Sotnikov and Chaikova, 2023)

Liu and Chilton (2022) identified guidelines for prompting when generating images in specific styles (using the prompt structure 'SUBJECT in the style of STYLE'). Those include focusing on keywords rather than prompt phrasing and pairing subject and styles that are relevant to each other.

To a certain extent, the quality and clarity of prompts should help achieve consistent results. Still, prompts that are simple in structure and relatively unambiguous in meaning could eventually result in undesired outcomes. The work of Chefer *et al.* (2023) proposes an intervention in the generative process to avoid deviations from the original intention of prompts that should be straightforward (e.g. a prompt for 'a turtle in a yellow bowl' that actually outputs a picture of a yellow bowl). In that case, output is made more accurate through a better interpretation of the prompt, rather than successive iterations and careful prompt engineering. An alternative solution was proposed by Wang *et al.* (Wang, Shen and Lim, 2023), who developed a system to automatically refine prompts generated in natural language, providing clearer instructions for AI image generators. Interestingly, results show that a strategy found to improve image generation was transforming first-person perspectives into third-person ones. In a way, such a strategy applies to prompt engineering the sense of objectivity discussed by Daston and Galison (2010), according to which a scientist's greatest virtue became removing themselves from the experiment.

There are, on the other hand, different, less objective approaches to prompting. Revel (Revell, 2022) describes experiments with image generator DALL-E where prompts (created either by the author or by GPT text generator) are of a literary or poetic quality. Chen and Kao (Chen and Kao, 2022) combine this poetic take with a more traditional approach, prompting verses from a traditional Chinese poem followed by a description of the desired illustration style. Such a degree of freedom seems quite distant from the objectivity required by scientific software.

4.1.1 Preliminary research

We have asked computational scientists and GenAI users how much their work depends on textual instructions, and how precise those instructions should be. Answers from both computational scientists and GenAI users were somewhat similar (Figure 2), expressing their dependency on textual interfaces and the need for entering clear instructions. GenAI users seem, in that case, aware of the importance of prompt engineering – and possibly confident that the correct structure of their prompts will influence results.

A computational scientist used an open question to justify his answer and express his preferences:

'[specific syntax] reduces space for "miscommunication" with the system, but I wouldn't mind a looser syntax or structure if I could still do my work effectively and avoid such miscommunication.'
(SS user 09)

A similar opinion was expressed by a GenAI user:

'For me it's important to be grammatically accurate and would like prompting by tool to help express, I'd like to collaborate and create through conversation more than code like text.'
(GenAI user 01)

Perceived importance of ease of use by the two communities were also somewhat similar (Figure 2), with GenAI users slightly more concerned about it.

Some comments suggest the interests of those communities converge: on the one hand, more complex GenAI would be tolerated.

'Not all Ai tools are easy to use.'
(GenAI user 22)

'Some tools are easier to use than others. It's about learning new skills to enhance the way you work.'
(GenAI user 19)

On the other hand, scientific software could be easier (even though that could involve trade-offs):

'Ease of use is a trade off, often, against power or utility.'
(SS user 85)

'Ease of use and consistency of syntax are nice, but I'm flexible enough to deal with it if it is not possible.'
(SS user 47)

'Easy to use tools: only if they do not hide the science'
(SS user 15)

The final comment is particularly relevant, as in scientific software, ease of use is always second to, or in service of, values we will discuss next.

4.2 Correctness, Openness and Reproducibility

A frequent topic when discussing scientific software is the importance of correctness of the software at all phases (Heaton and Carver, 2015), and the reproducibility that supports its case (Hinsen, 2013). Reproducibility - the capacity of separate groups of scientists to achieve the same results by following the same methods with the same data - is a major concern in computational science (Krafczyk *et al.*, 2019), and a major reason for scientific data and software to be made openly available, as well as configuration files that could help reproducing the original experiment's environment and procedures. Correctness, then, is intimately related to reproducibility and openness in scientific software. Indeed, the origins of the open-source software movement can be traced back to scientific software communities in the 1950s (Dongarra *et al.*, 2008). Such is the opposite of the black-box approach adopted by most commercial software companies, including many Generative AI

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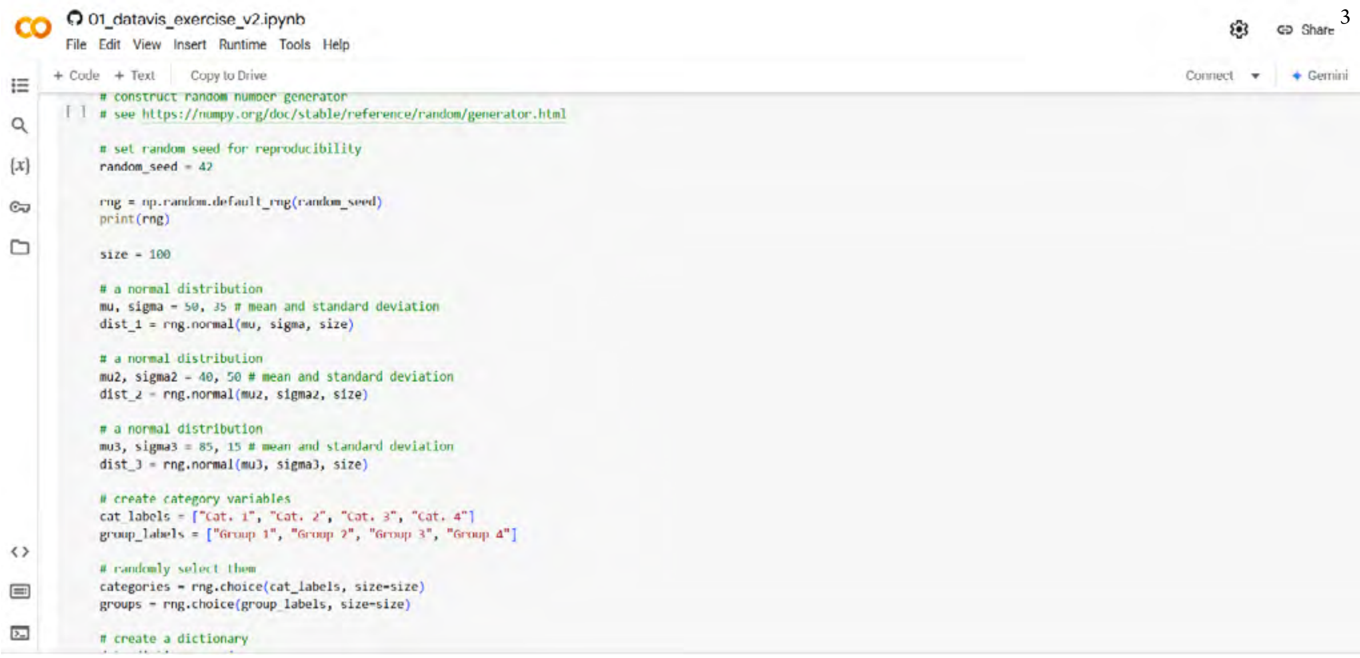

ones, where models and data are kept closed and inaccessible for scrutiny.

Not surprisingly, then, scientific representation and illustration is one of the fields where the lack of correctness can be easily identifiable. Strickland *et al.* (2022) discussed how scientific illustrations generated by generic LLM tools from prompts can ignore requirements for generating the output (exemplified by out-of-scale illustrations of the solar system) – a problem faced first-hand by Thurzo *et al.* (2023) when attempting to generate anatomically correct views of a skull and teeth. The generation of incorrect AI images is also a problem for databases of synthetic images. Ali, Murad and Shah (2023) trained a Generative AI system to create images of x-rays and computerised tomography of lungs, and observed how even systems that were pre-trained on expert scientific imaging often outputs images that can be promptly identified as incorrect by specialists. A similar approach was taken by Abduljawad and Alsamani (2022), who compared different image generators to create synthetic images for training remote sensing systems (for instance, satellite images to detect activities in deserted areas). In the field of scientific illustration, there is a rising number of papers featuring incorrect imagery, the most infamous case having been retracted (Guo, Dong and Hao, 2024).

At first sight, correctness would not seem to be so critical in all cases of GenAI images for art and design purposes: more often than not, illustrators and designers could be concerned about images that look correct enough, or even just interesting (as we'll discuss later). Yet, there are cases for correctness in art and design too: craft educators surveyed by Vartiainen and Tedre (2023), for instance, feared that absence of design constraints from AI-generated images (for instance, properties of materials used for designing artefacts) could misinform users about the real-world limitations of their designs.

Consistent visual styles aside, reproducibility – in the sense of output duplication by

Figure 3 Code for reproducibility on Google Colab platform (Murphy Quinlan, no date).

third parties – might not be a particular requirement in art and design. Arguably, the power to reproduce any generated image could threaten the value of intellectual property (if there is such thing when it comes to generative AI art). Even though prompts can be elaborated using natural language only, some GenAI systems allow for the use of parameters to achieve reproducibility and, therefore, visual consistency. According to MidJourney's documentation, 'Seed numbers are generated randomly for each image but can be specified with the seed parameter. If you use the same seed number and prompt, you will get similar final images' (Midjourney Command List, no date). Altering the seed number could be used, then, for fine-tuning outputs (or radically changing them), as well as exploring the potential outcomes from a single prompt - Liu and Chilton (2022) suggest between three and nine different seeds as a good number. This use of seed numbers is not different to the ones used in scientific software for reproducibility of synthetic data (Figure 3).

4.2.1 Preliminary Research

Reproducibility, openness and correctness (expressed as a 'reflection of the real world') were significantly more important amongst members of computational science than GenAI art (Figure 2).

Some of the comments reinforce the contrast between the search for an objective knowledge and free exploration of representation forms.

'I do verification and validation studies for any software I use so I check the "accurately reflect real world" anyway. I would never trust a software blindly.'
(SS user 41)

'I am a computational physicist by training so develop and run models of physical systems so want them to be representative of the real world as best as reasonably practical.'
(SS user 78)

'In what ways can my work accurately reflect the real world? Nor am I interested in doing so.'
(GenAI user 16)

'I don't want my work to be replicable. I think my work is art and it should be unique'
(GenAI user 92)

'I do not want full control over the tool and the fact that it is a black box is interesting to me. The images I create in Midjourney do not accurately represent the real world.'
(GenAI user 15)

Next, we turn to a topic expressed by some GenAI users' comments: the free exploration of unique possibilities.

4.3 Experimentation, Creativity and Free Manipulation

There are particularities of computational science that might seem advantageous when compared to its traditional, lab-based counterpart. Computational science allows scientists to conduct research that would have been, otherwise, extremely impractical or even impossible (Segal and Morris, 2008). The expression of scientific models and concepts in code, and their simulation and representation within the software, provide a space for experimentation that could be explored with a significant degree of freedom and flexibility in search of new insights, from initial modelling and conceptualisation to final results and data analysis. In that sense, scientific software is a rigorous, scholarly expression of the computer as an 'object to think with' proposed by Turkle (2005).

Generative AI tools those can foster a process similar to that in art and design. Bender (2023), for instance, proposes the use of GenAI image generators by media students, who engaged in iterative prompting not to obtain a final design outcome, but to convey creative intentions to their work groups – a goal similar to Vartiainen and Tedre's idea of *externalisation*: being able to render mental images for further discussion with students, which would be distinct to *ideation* – the process of generating ideas – itself (Vartiainen and Tedre, 2023). Davis *et al.* (2023), on the other hand, demonstrated how an open-source and a custom-built AI image generator both support divergent and convergent thinking, expanding users' imagination in different stages of the fashion design process, by providing images for reference and inspiration, interpolating different designs, and helping visualise intended final design outcomes. The design process seems, then, enhanced by the tension between method and chance in generative models which, as described by Bryne, 'seem to offer the user something between an experience of finding just-the-thing they are looking for and the chance of serendipitous discovery' (Byrne, 2023, p. 375). Negative comments, on the other hand, expose how users perceived the accuracy of AI generated content as a limitation that left 'no room for the imagination' (Davis *et al.*, 2023, p. 7). This perception touches on a separate topic discussed by Vartiainen and Tedre (2023): the *black-boxing of creativity*, i.e., the opaqueness of the processes that generate the design outcome from the initial prompt.

The contrast between GenAI's text-based approach and traditional graphic user interfaces used by artists and designers is emphasised by Liu (2023) and Liu *et al.* (2022), who propose multimodal interfaces for the manipulation of three-dimensional AI generated content and news illustrations, respectively. Liu considers the text-based interfaces 'a fundamental inversion of what many artists are traditionally used to: having full control over the composition of their work' (Liu, 2023, p. 1). On the one hand, the assessment makes sense: different types of design software, from image editor Adobe Photoshop to 3D modeller 3DS Max, to UX prototyping Figma, rely on Graphical User Interfaces that make the manipulation of those tools intuitive. Yet, when Computer-Aided Design software is considered, command-line interfaces are often the tool of choice for control and precision. A similar argument could be made about scripting tools for 3D modelling software such as Blender and Maya, which allow for the procedural creation of scenes and objects that would take much longer to be generated and manipulated manually. Conversely, science-oriented programming tools such as Spyder and scientific software such as MatLab, Origin and LabView provide GUIs (and in some cases, the tools to create additional GUIs) for increased ease of use. This hybrid, multimodal approach, as the one proposed by Liu (2023), is also present in GenAI open source and commercial solutions such as Stable Diffusion and Adobe Firefly, which provide GUIs to extend or simplify access to both frequently used and advanced functionalities for increased control over the final outcome.

4.3.1 Preliminary Research

Survey results show an interesting trend: computational scientists are slightly more concerned about control over tool and final output, but less concerned about results meeting their expectations than GenAI users (Figure 2). It would seem, then, that many scientists treat unexpected results as an integral (and in fact, desirable) part of a controlled process, whereas some GenAI users might forfeit their agency and hope for black-boxed serendipity (or use other tools for further control).

'I rely on GUIs to fine-tune work produced with AI, text and image. And vice versa to varying degrees.' (GenAI user 20)

'I am very interested in the element of chance which exists with my use of AI. I am not interested in producing something which I can predict.'
(GenAI user 15)

'Unexpected results are a part of scientific research, so I don't mind if I get them.'
(SS user 04)

'Results should not always be what you expect when you are performing research.'
(SS user 05)

'I am neutral on whether results should be exactly what I'd expect, as unexpected results may open an unexpected avenue of research.'
(SS user 11)

4.4 Domains, Communities and Ethics

Both scientific software and Generative AI tools have been, so far, described in quite generic terms. However, specialised tools dedicated to specific domains are common in computational science and, to a lesser degree, present in GenAI art tools. In that case, despite the high number of software that can be used by scientists of different specialist areas (e.g., MatLab; Origin), there are software dedicated to areas such as micromagnetism (Beg, Lang and Fangohr, 2022), astrophysics (Auld, Bridges and Hobson, 2007) etc. Scientific practice is usually organised within specialist domains, their communities and paradigms (Kuhn and Hacking, 2012). Ultimately those communities and domain specialist areas will uphold the rules of correctness, workflows and so forth. The case for domain specialism and communities is not, so far, as strong or structured in GenAI. Those systems are usually generic solutions, capable of emulating styles and design outcomes from diverse media (photos, Illustrations, etc.), although there are occasional tools dedicated to specific *genres* and techniques, such as news illustrations and words-as-images (Liu, Qiao and Chilton, 2022; Iluz *et al.*, 2023). Moreover, some open-source AI generators allow for users to train and fine-tune their models and datasets, allowing for greater control over domains, topics and themes (Zhang, 2023).

Yet, the use of GenAI can foster a sense of community and take advantage of it: there is a social nature to prompting, as communities help each other, learning by sharing examples and techniques (Repenning and Grabowski, 2023). A playful exploration of that sense of collective prompt-building is described by Villareale, Cimolino and Gomme (2023) who designed a game that challenged players to generate images representing specific entities without including an explicit reference to that entity in the prompt (e.g. generate an image of the Superman character without using the word 'Superman'). The collective and iterative nature of that game helped develop better prompts from users' mental models. Such an experiment serves as an interesting analogy of computational science and its community, which have developed over decades relying on peer review and collaborative efforts towards better computational models and simulations to express all types of phenomena.

Artists, designers and the AI community at large often express reservations regarding the ethics of generative AI (Bender *et al.*, 2021; Byrne, 2023; Marcus and Southen, 2024). Frequently, negative perceptions concern the lack of transparency regarding image generation process and datasets used for training models, which could be training on copyrighted material to generate art that unduly appropriates from artists' original works and style (Vartiainen and Tedre, 2023). Solutions aiming at fair authorship attribution could facilitate fair and ethical ways for attributing authorship, identifying particular images from datasets that inform images generated by AI (Koziol, 2023). If adopted at larger scales, that could make generative AI more transparent in similar ways to open science/open data. Still, the threat to professional artists and overall devaluation of human creativity would still be moral issues worth considering (Zylinska, 2023). Ethical issues in generative art and machine learning go beyond copyright issues and dataset transparency, including biases that could arise from statistical methods used in GenAI, which seemed to have partially stemmed from Eugenics:

> [T]he fact that these techniques underpinning machine learning were developed within explicitly eugenicist programs of research—on heredity, biometrics, etc.—should (at the very least) encourage some pause and critical reflection on the implications of their use in design. (Byrne, 2023, p. 377)

Indeed, biases from datasets and processes behind their statistical analysis are also a concern for craft educators (Vartiainen and Tedre, 2023), and media researchers (Thomas and Thomson, 2023). An additional ethical concern is the use of GenAI to generate *deepfakes*, fabricated photographs of real persons in situations that did not happen. Arguably a problem as old as photo manipulation, it is aggravated by the quality and speed at which AI can produce fake imagery. Hunt (2023) compared award-winning weather photographs to AI-generated images, challenging readers to identify real photos from fake ones. Preliminary results from LLM models themselves might be more capable than humans in detecting this type of forgery, by identifying 'fingerprints' in those images that differ from actual photographs (Papa *et al.*, 2023). A similar study was conducted on the detection of painting forgery (Fraile-Narváez, Sagredo-Olivenza and McGowan, 2022). There might be a case, then, for the deliberate inclusion of 'fingerprints' in images generated by ethical AI tools.

Although It would be naïve to hold the scientific and academic community as a perfect role model for ethics, the structure of those communities, capable of ensuring a fair amount of fairness and best practices around their domains and methods could serve as inspiration for their GenAI counterparts.

4.4.1 Preliminary Research

Ethics, support from community and specialist knowledge - all of which could be considered cornerstones of scientific practice - are slightly, but perceptually, less valued by GenAI users than by computational scientists (Figure 2). Consideration on ethics from GenAI users usually focused on authorship attribution and copyright.

> *'Being ethical in my design work is important to me particular in regards to attribution.'*
> *(GenAI user 21)*

> *'I think with using AI tools it's very obvious that specific people's work is being drawn from, and it would be great for the tool to credit these data samples it has used.'*
> *(GenAI user 11)*

> *'I think morality is not important, copying is normal,'*
> *(GenAI user 31).*

5. Conclusion and Further Agenda

Findings and discussion, including potential venues for further research and design initiatives, can be mapped back into the study's research questions:

> ***Q1***: How do computational science and generative art and design differ in terms of their goals, requirements and values?

Correctness, reproducibility and openness seem to be significantly more valued in computational science than in Generative AI. The opaqueness of image generation, from datasets to models, conflates ethical and creative issues. In that case, the lack of transparency might hinder the generation of outcomes that are genuinely original and informed by conscious design decisions. Openness, then, could lead to better models and datasets, that would then lead to better (and more ethical) design outcomes. Taking the image presented in Figure 1 as an example, by accessing datasets and models, users would be able to investigate why design outcomes correctly attempt to simulate the pointillism and chromoluminarism that characterise Seurat's paintings, but somewhat fall short of reproducing the look and feel of natural media – in which case they could try different prompting strategies or model fine-tuning.

> ***Q2:*** How do approaches to text-oriented UI compare between scientific software and generative art and design?

Computational science is significantly stricter, requiring much more precise commanding and programming than Generative AI tools. As some examples illustrate, prompt engineering already allows for the use of parameters in a similar way to programming languages and might evolve into something with greater levels of control (those tools, after all, are primarily developed by technology professionals), as well as adopt other UI solutions typical from scientific software (for instance, visual programming/diagramming tools).

On the other hand, scientific software could become easier to use if it adopts GenAI paradigms as reference (we also note that some computational science tools, such as Google Colab, already incorporate AI agents for programming assistance). Moreover, scientific software could adopt strategies to encourage what Bryne (2023) described as the *serendipity* and *just-the-thing* materialised generative AI outcomes. That could reinforce an intuitive approach which is already present in scientific practice, but not as supported by scientific software as reasoning is. Strategies to achieve that could include greater flexibility in programming and the use of prompting in natural language.

> ***Q3:*** What practices and principles from scientific software could benefit generative AI and vice versa?

Despite facing its own challenges concerning academic malpractice and use of fake AI-generated images (Kwon, 2024), the scientific community could serve as role model for GenAI art communities - particularly those concerning art and design professionals - who could potentially learn from computational scientists' ways of protecting their community, defend their domain of expertise, and advocate for ethical and open approaches to AI tool development. Artists and designers should claim ways of having more voice on how those tools are structured, curated, used and designed, as well as investigate ways of mitigating their impact on the creative economy workforce, including compensation, authorship attribution, or subsidy to organisations supporting arts education, production and funding.

Acknowledgements

The author would like to thank the editorial team and reviewers for their help in improving this paper, Billy Kirby and Ningtao Mao for their help with corn seed funding, Rui Leitão for his input on questionnaire design, Lauren Machon for her help with focus group arrangement and planning, Elif Şener and Ben Bradley for focused writing sessions, Maeve Murphy Quinlan for assistance with graph generation, the Leeds University Business School and the School of Design. This research received ethical approval from the University of Leeds Research Ethics Committee, code LTDESN-200.

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